Deployment of Privacy-Preserving Machine Learning for Political Polling in the 2024 Presidential Election

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Overview

- We build a system for securely predicting political preferences from web browsing data
- We collect and analyze data from almost 8000 unique users
- All analysis takes place under MPC

Roadmap

1. Motivation

2. System Design

3. Learning Algorithm

4. Lessons Learned and Future Directions

Motivation

Background

- Web browsing behavior can predict voting results
- Quantifying the 'Comey letter' (Comarela et al.)
  - The event was too close to the election for other polling methods to detect the effect

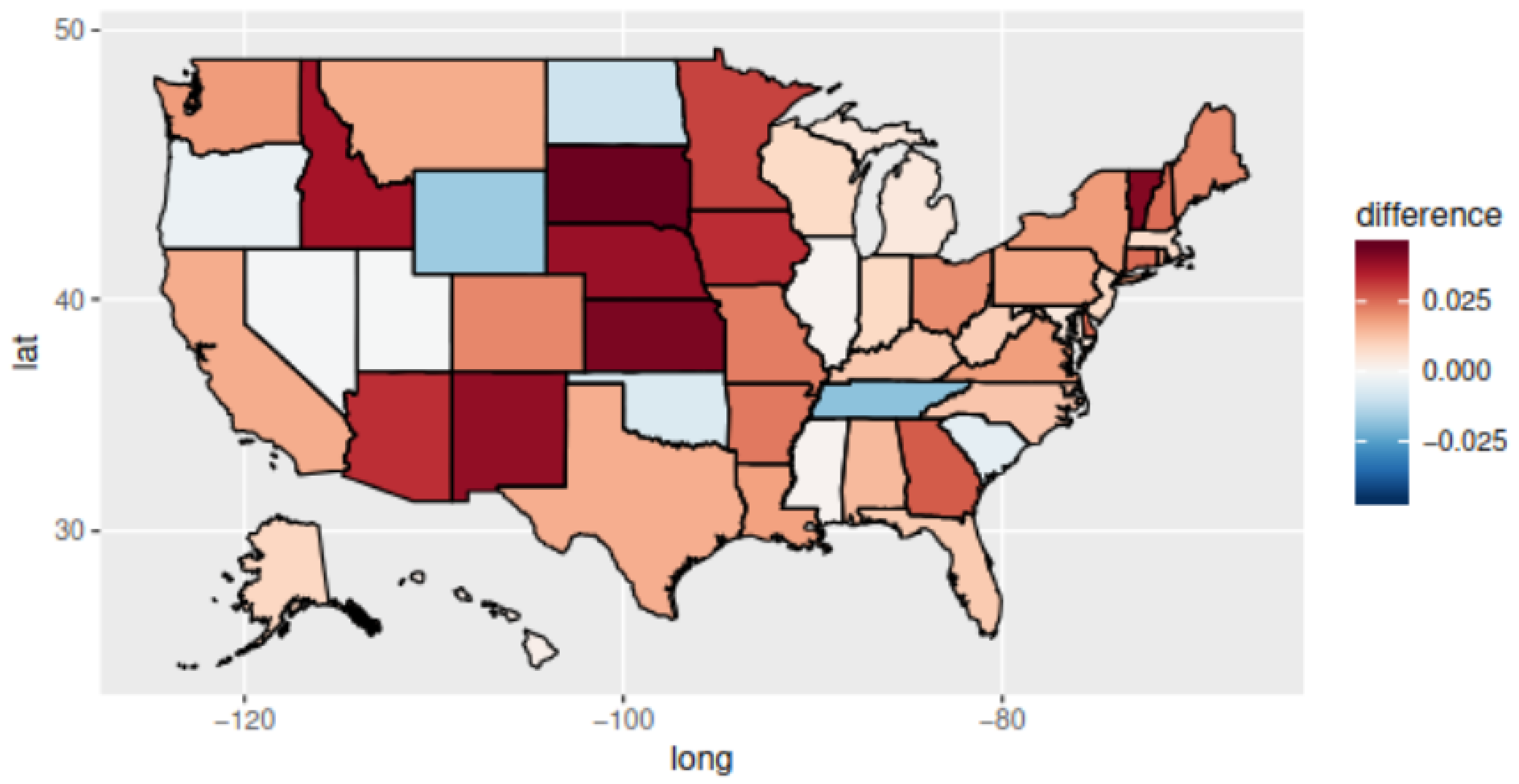


Figure 8: Impact of the 'Comey letter' at the state level.

Traditional Political Polling

- Data collection takes time
  - High latency between poll commission and results
- Human-intensive data collection
  - Scaling to collect much more data would be costly
- Poor geographic and temporal coverage
  - Results are concentrated in key regions immediately before an election
  - Many locations go unpolled, particularly early in an election cycle

West Virginia 2024 Presidential Election Polls

Harris vs. Trump

Source	Date	Sample	Harris	Trump	Other
Research America	8/30/2024	400 LV ±4.9%	34%	61%	5%

Michigan 2024 Presidential Election Polls

Instantly compare a poll to prior one by same pollster

Harris vs. Trump

Source	Date	Sample	Harris	Trump	Other
Average of 23 Polls†			48.6%	46.8%	-
FAU / Mainstreet	11/04/2024	713 LV	49%	47%	4%
Emerson College	11/04/2024	790 LV ±3.4%	50%	48%	2%
Research Co.	11/04/2024	450 LV ±4.6%	49%	47%	4%
InsiderAdvantage	11/03/2024	800 LV ±3.7%	47%	47%	6%
Trafalgar Group	11/03/2024	1,079 LV ±2.9%	47%	48%	5%
MIRS / Mich. News Source	11/03/2024	585 LV ±4%	50%	48%	2%
NY Times / Siena College	11/03/2024	998 LV ±3.7%	47%	47%	6%
Morning Consult	11/03/2024	1,108 LV ±3%	49%	48%	3%
AtlasIntel	11/02/2024	1,198 LV ±3%	48%	50%	2%
Redfield & Wilton	11/01/2024	1,731 LV ±2.2%	47%	47%	6%
The Times (UK) / YouGov	11/01/2024	942 LV ±3.9%	48%	45%	7%
EPIC-MRA	11/01/2024	600 LV ±4%	48%	45%	7%
Marist Poll	11/01/2024	1,214 LV ±3.5%	51%	48%	1%
AtlasIntel	10/31/2024	1,136 LV ±3%	49%	49%	2%
Echelon Insights	10/31/2024	600 LV ±4.4%	48%	48%	4%
MIRS / Mich. News Source	10/31/2024	1,117 LV ±2.5%	47%	49%	4%
UMass Lowell	10/31/2024	600 LV ±4.5%	49%	45%	6%
Washington Post	10/31/2024	1,003 LV ±3.7%	47%	46%	7%
Fox News	10/30/2024	988 LV ±3%	49%	49%	2%
CNN	10/30/2024	726 LV ±4.7%	48%	43%	9%
Suffolk University	10/30/2024	500 LV ±4.4%	47%	47%	6%

Two Approaches to Political Polling

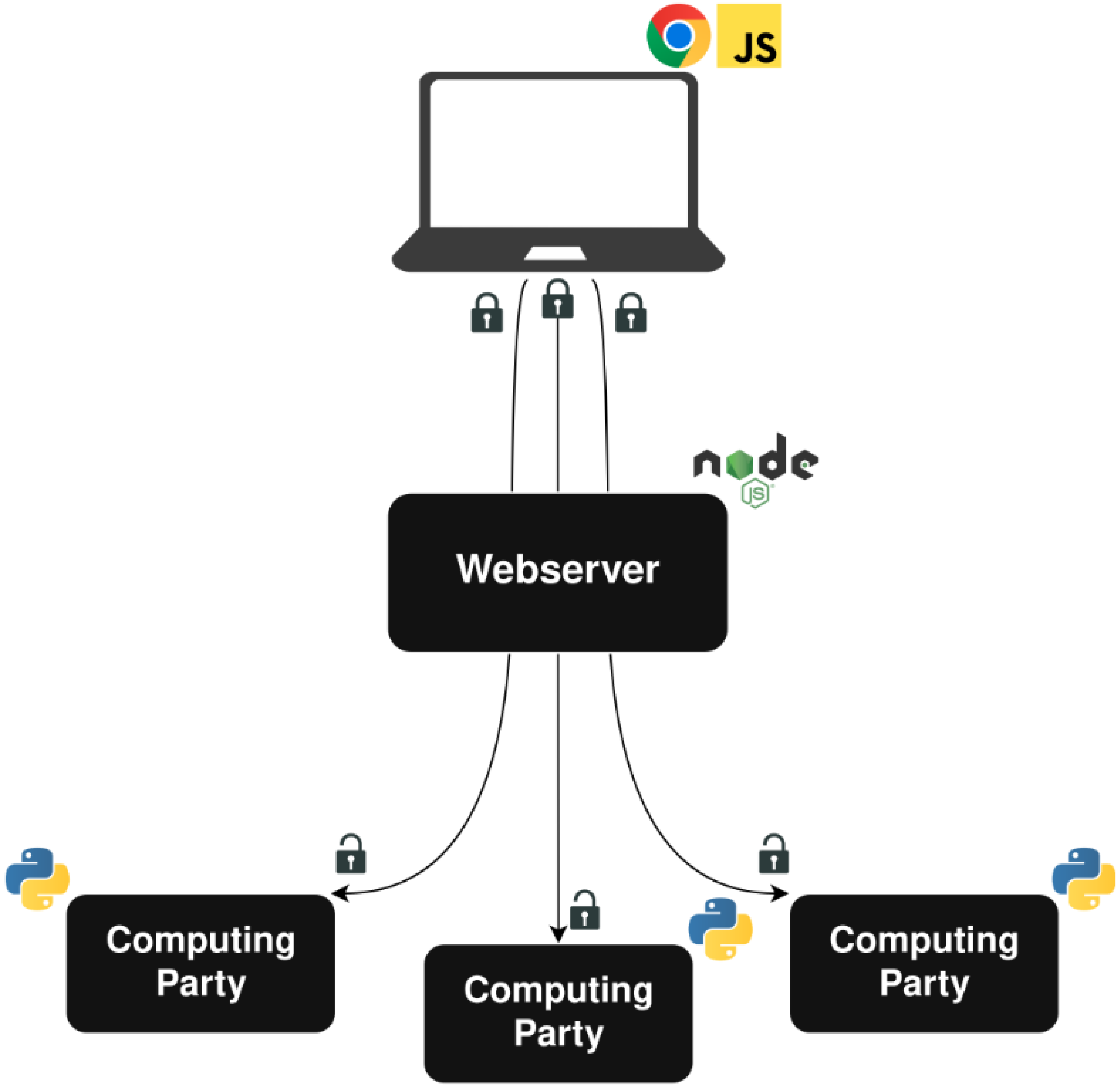
Traditional Polling		Web Behavior Analysis
Slow	VS	Immediate
Expensive		Cheap
Coarse-grained insights		Fine-grained insights

What about privacy?

System Design

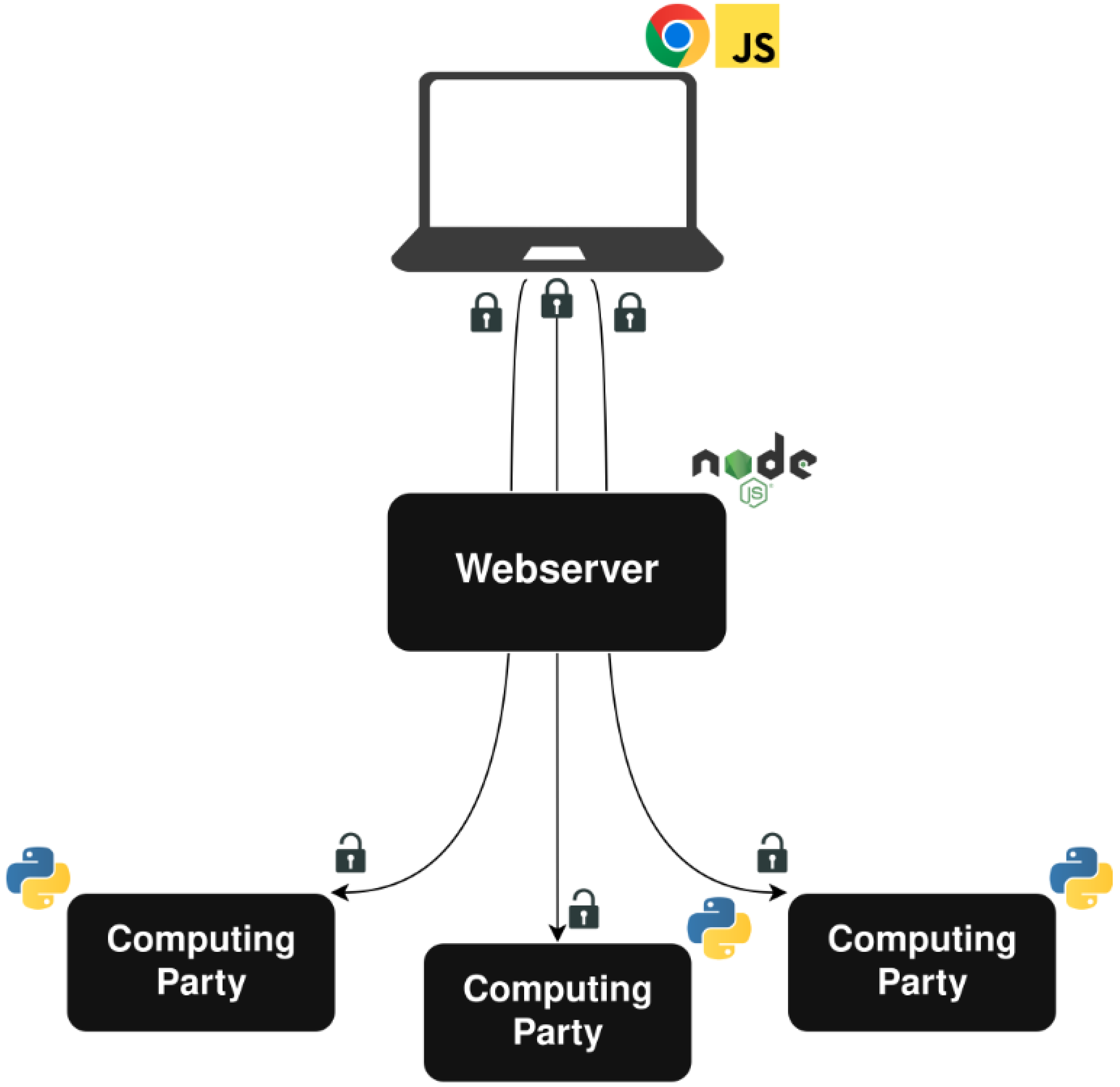
Three Components

- Client Plugin
- Webserver
- MPC Backend



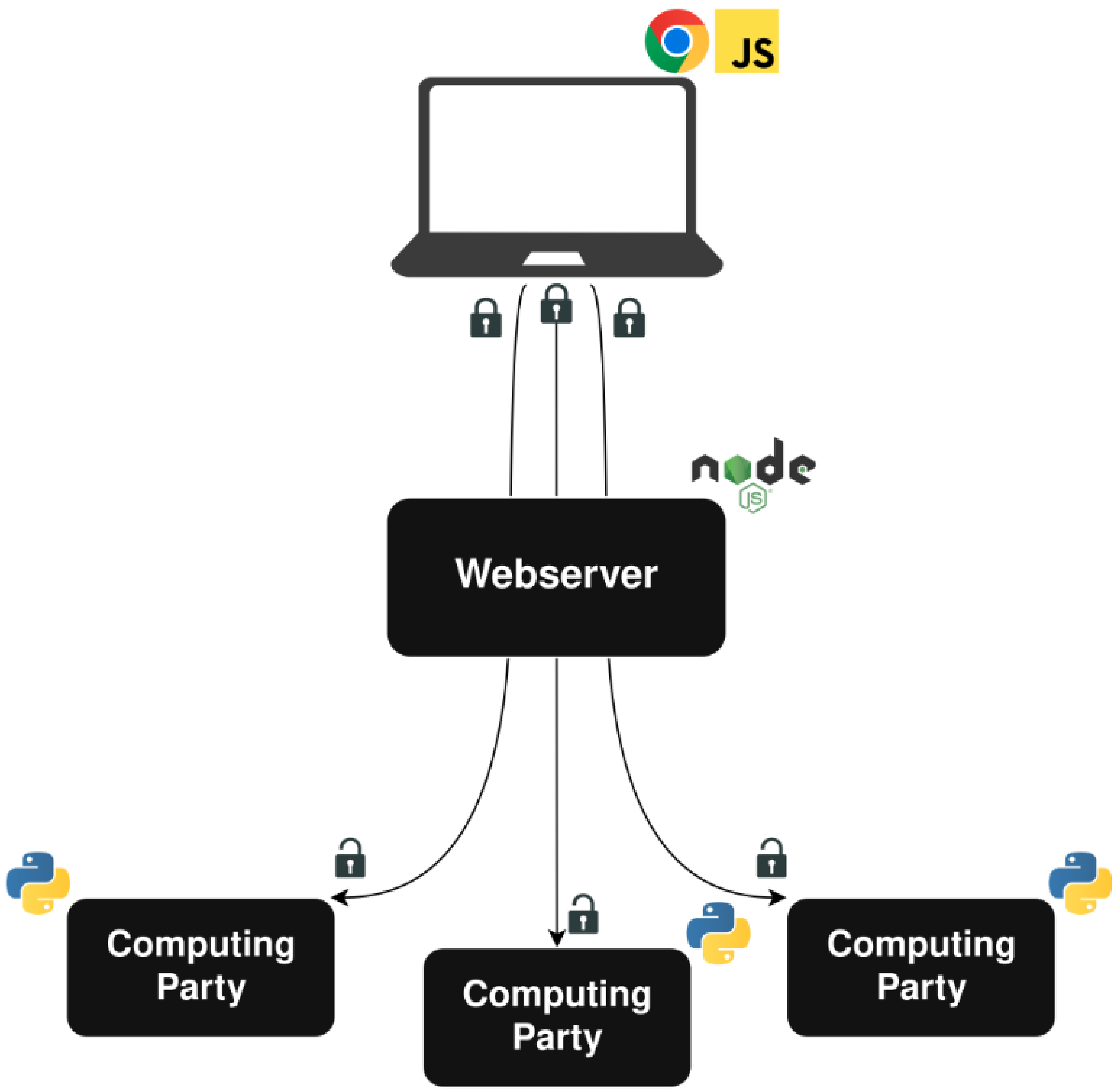
Client Plugin

- Custom-built Chrome plugin to monitor browsing
  - Tracks visits to top websites
  - Tracks referrals to top websites from social media sites
- Daily data uploads of secret-shared histograms
- Client-side secret sharing and encryption
- Implementation is open source



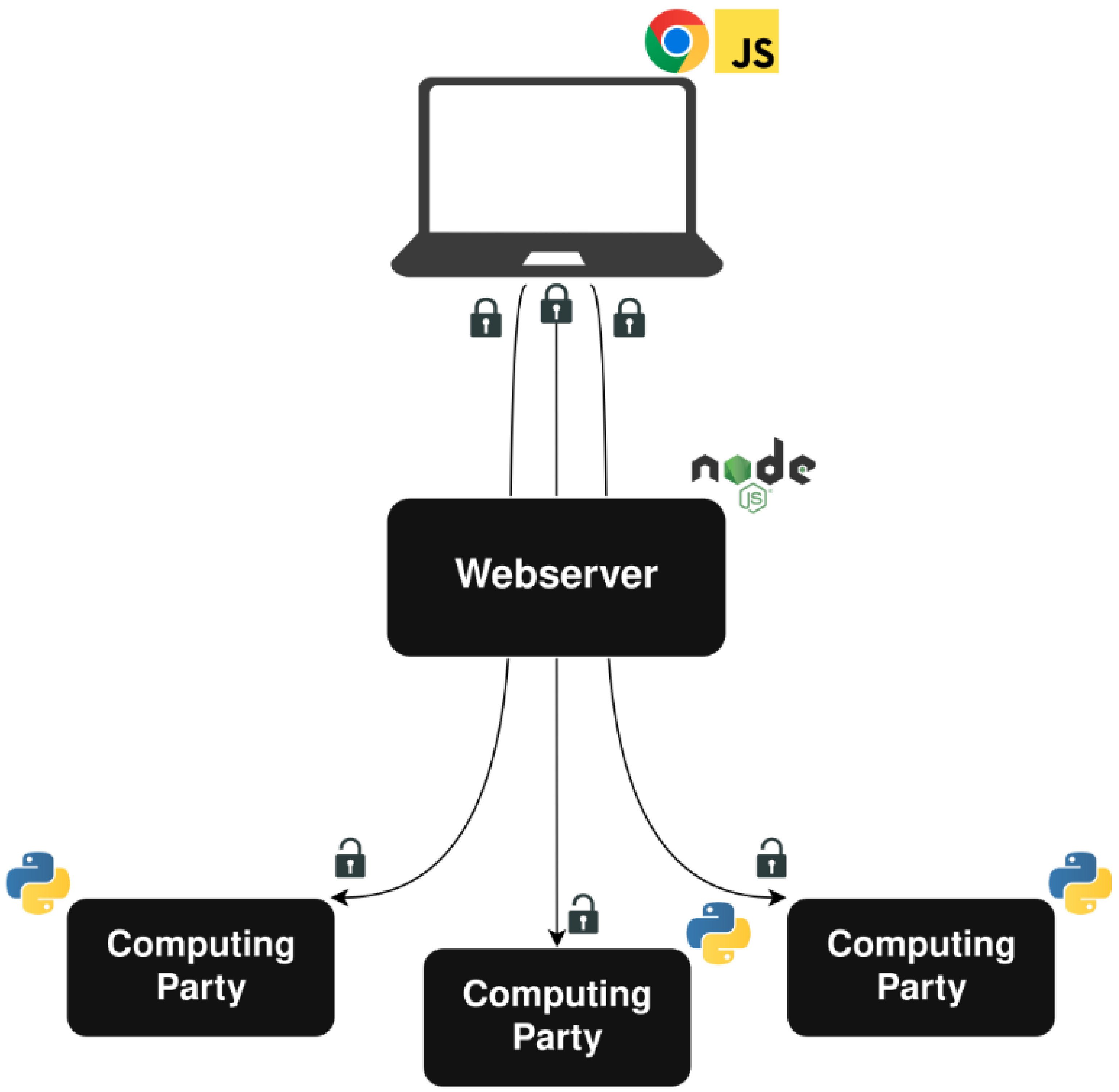
Webserver

- Simplifies interaction with clients
- Collects basic metadata
  - For payment and location tracking
- Never sees any private data
  - Secret-shares are end-to-end encrypted to the parties



MPC Backend

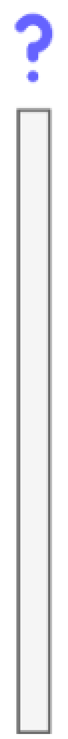
- Threat model
  - Three parties
  - Semi-honest security
  - One adversary
- We use and augment the CrypTen library
- Code will be available in the future

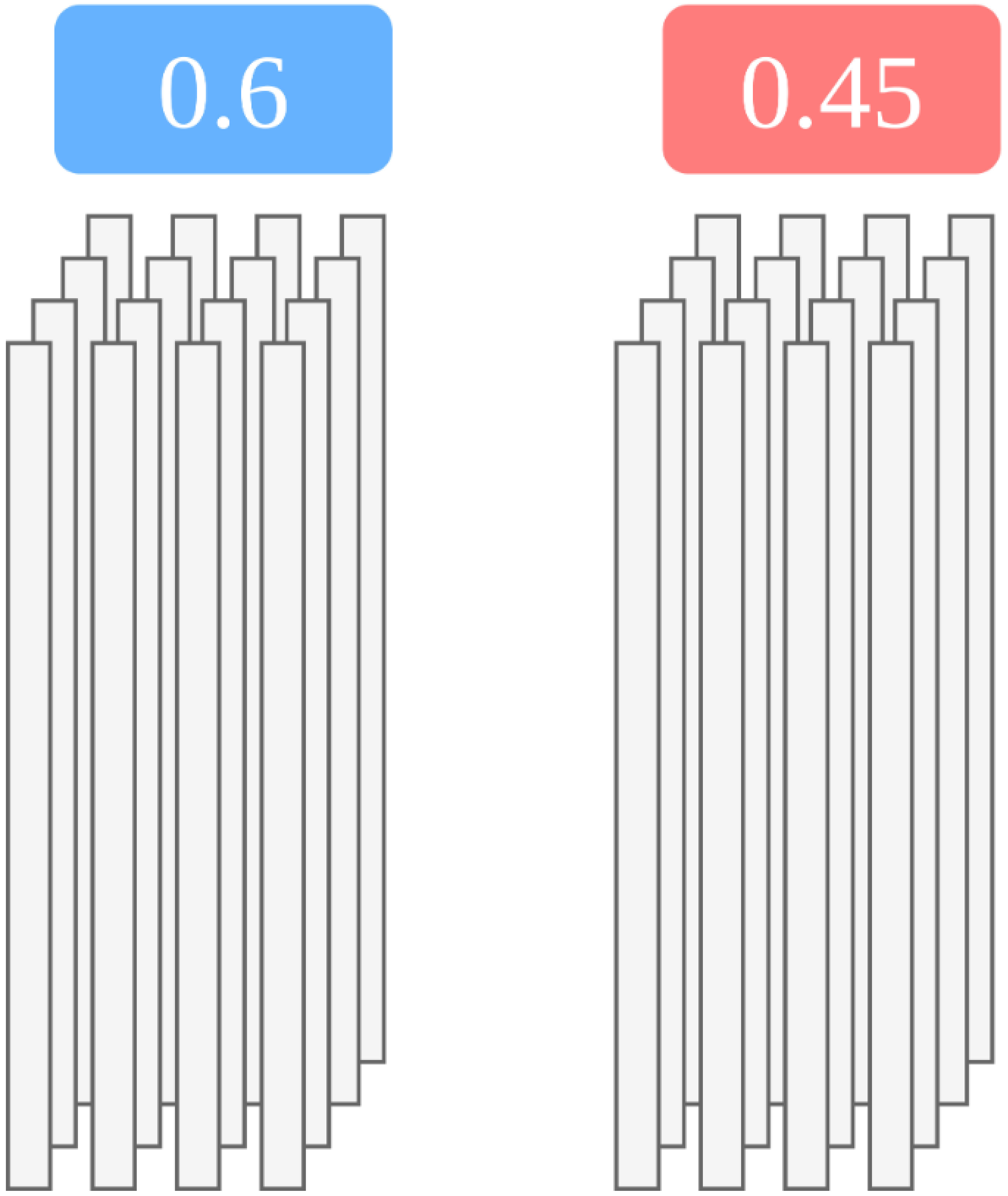


The Learning Process

Learning from Label Proportions (LLP)

- Each user uploads an *unlabeled* 1,034-element vector every day
  - Number of visits to the top 517 sites
  - Number of social media referrals to the top 517 sites
- Unlabeled vectors are grouped by state
- Each state has a ground-truth label
- Train on aggregate ground truth
- Predict on an individual level





The Learning Algorithm

Input: visit and referral histograms grouped by state, state-level ground truth

Train–update loop until convergence

- Assign initial predictions to each individual
- Train a logistic regression model on current predictions
- Compute new predictions
  - Sort each state's users by prediction
  - Set a threshold so the aggregate state prediction matches state ground truth
  - Assign updated individual predictions according to the threshold
- Repeat until predictions converge

Implementation in MPC

- Initial label assignment can be performed in plaintext
- Training a logistic regression model is implemented in CrypTen
  - Logistic regression is supported out-of-the-box
- Computing thresholds requires oblivious sorting
  - We implement Bitonic sort using CrypTen's secure primitives
  - The most expensive piece of the computation
- Updated label assignment and convergence checking use secure comparisons
- Practically efficient
  - All computation completed in a few hours at most

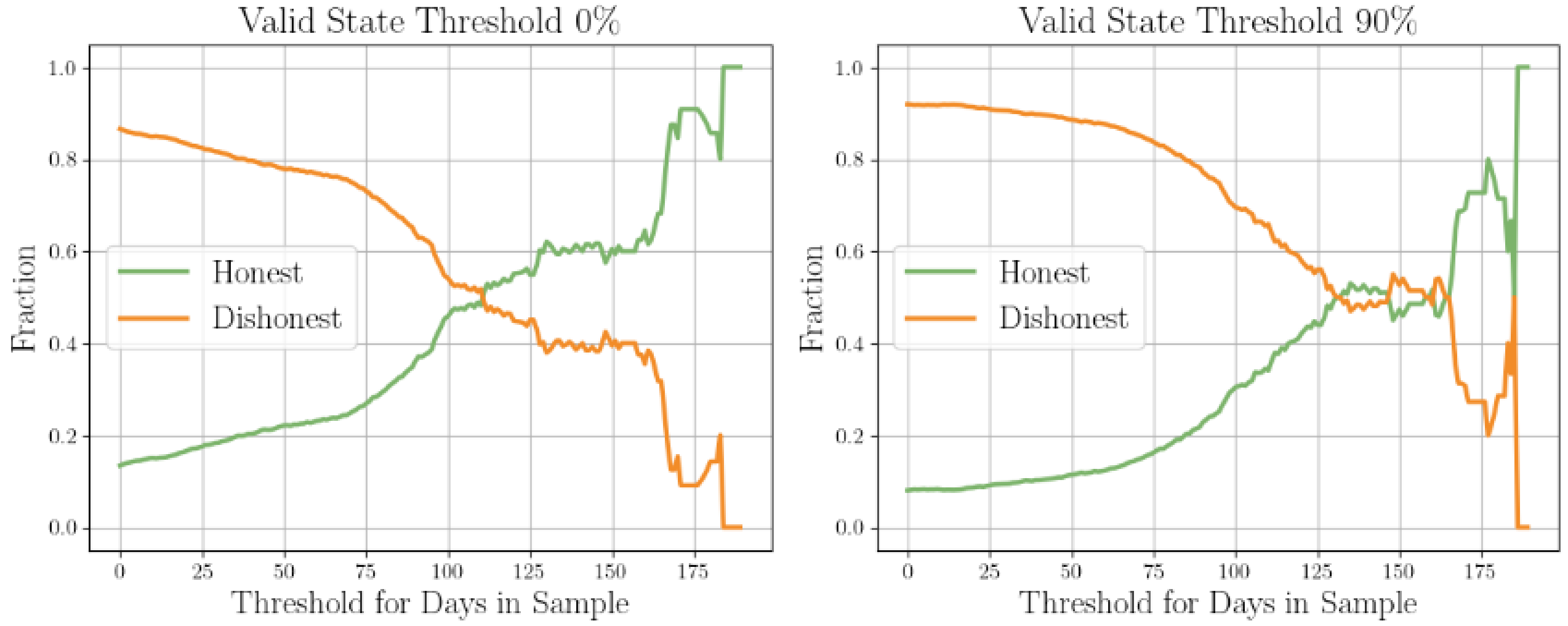
Lessons Learned and Future Directions

Data Integrity Matters

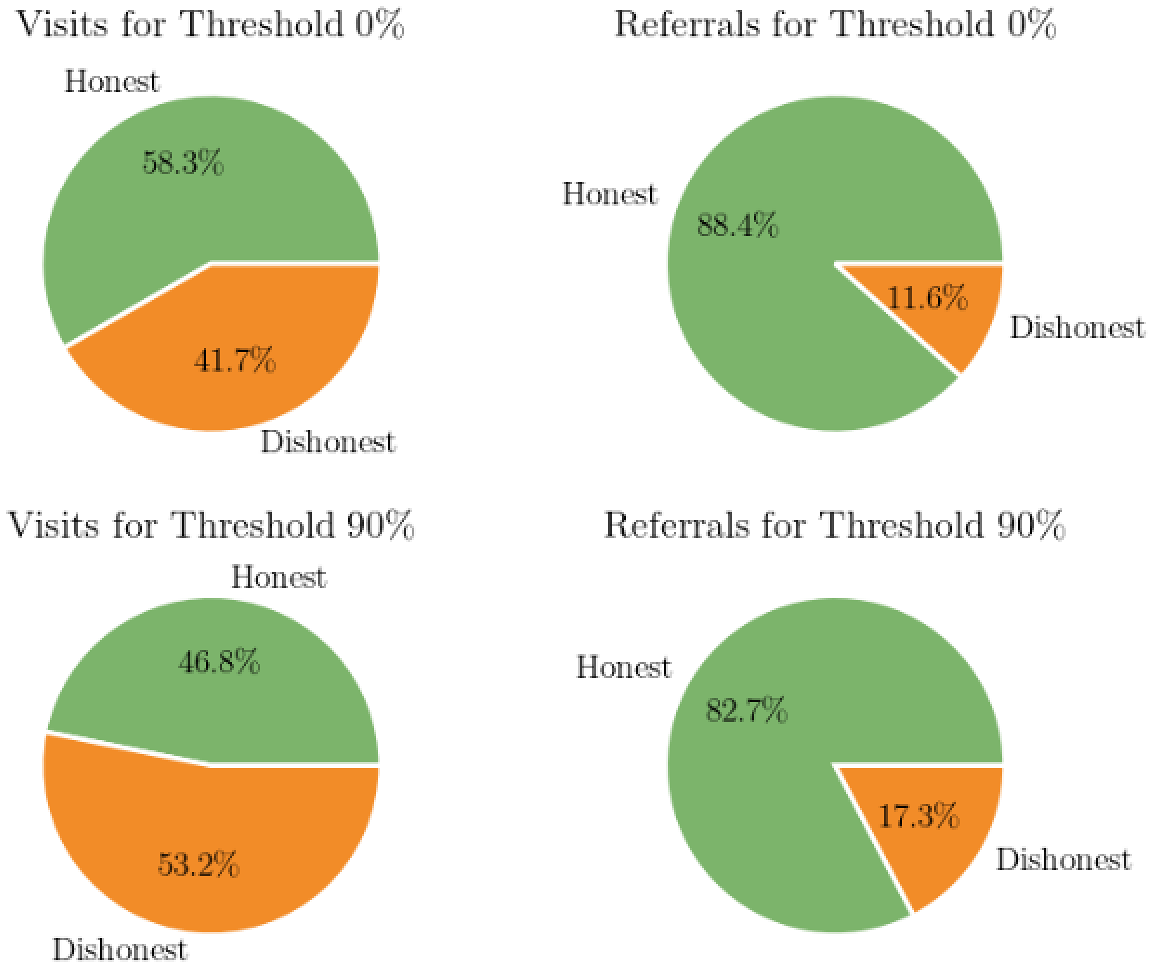
- Our initial advertisement targeted users in the swing states
  - Incentive to report location dishonestly
- We use IP addresses and geolocation data to validate the data
  - 98% of users are located in the United States
- State-level results are concerning
  - 85% of users reported their state dishonestly
  - 15% of users reported an invalid ZIP code for their state

Digging Deeper on the Data

- Users in the sample for longer are more honest
  - Ephemeral dishonest users, consistent honest users



- Honest users contribute much richer data
  - Referral data provides the best signal (Comarela et al.)



Data Integrity

Lesson: Validating and enforcing user honesty should be a priority in future deployments.

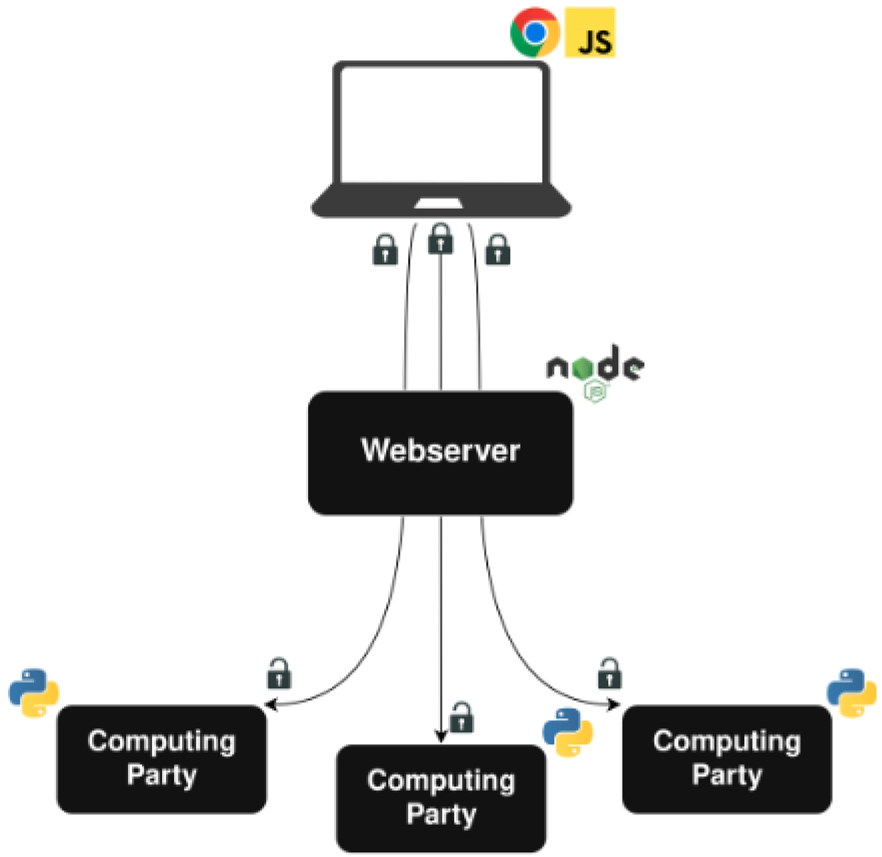
Lesson: Our learning process is surprisingly robust to dishonest users.

Opportunity — Privacy-Preserving Location Verification

- A difficult problem, even without privacy
- Integrate cryptographic techniques with existing plaintext approaches

Strengthening the Threat Model

- AWS as a single point of failure
- Reduce or eliminate trust in the core computation
  - Incorporate external organizations in the MPC
  - Explore different cryptographic primitives
- Anonymous payments



Thank You!

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